A THEORETICAL METHOD TO QUICKLY IDENTIFY MULTIPLE CONSTANT CONTAMINANT SOURCES INDOORS BY LIMITED NUMBER OF IDEAL SENSORS

Hao CAI[2,1], Xianting LI[1], Lingjuan Kong[3], Xiaoliang Shao[1]
[1]School of Architecture, Tsinghua University, Beijing, P.R. China
[2]Engineering Institution of Engineering Corps, LA University of Science & Technology, Nanjing, P.R. China
[3]Nanjing Branch Campus of the PLA Artillery Institute, Nanjing, P.R. China

ABSTRACT

This study presents a theoretical method that can quickly and accurately identify the locations and strengths of multiple constant contaminant sources indoors by using a single or a limited number of ideal sensors. The method was numerically demonstrated and validated by case studies of sixteen scenarios of contaminant releases in a three-dimensional office. The effects of the number and positions of sensors used, total sampling time, and sampling intervals on the performance of identification were thoroughly studied. This study can help to develop methods for identifying multiple sources by using real sensors as well as optimizing the layout of sensors.

INTRODUCTION

In case of accidental or intentional releases of hazardous contaminant indoors, such as the biochemical terrorist attacks, epidemic outbreak, and toxic gas leakage, quickly identifying the characteristics (e.g., location and emission rate) of contaminant source in short time is critical for taking prompt response measures to protect occupants and mitigate losses.

The identification of contaminant source is an inverse problem compared to the prediction of contaminant dispersion,. Although much work has been conducted on the inverse problems in heat transfer (Alifanov, 1994), groundwater transport (Mahar and Datta, 2000), and atmospheric constituent transport (Seibert and Frank et al., 2002), only a little work has been published on the determination of indoor contaminant source. Liu and Zhai (2007) thoroughly reviewed various pollutant inverse modelling methods for both groundwater and air fields. The review indicated that although contaminants in groundwater and air follow the same transport rules, there are still great challenges related to air applications due to the significant property disparities between the two problems.

In practice, there are various ways for contaminants to be released into indoor environment. First, the number of sources may be single or multiple. Second, the releases may be instantaneous, or continuous with constant/changing rate. In addition, in some cases, the potential locations of sources are know, while in other cases the potential locations of sources may be totally unknown. For example, in terrorist attacks, hazardous agents may be released at any indoor locations. As a variety of scenarios exist, the research on source identification in indoor environment is full of challenges.

In recent years, several studies have been devoted to identify contaminant sources indoors. Sohn et al. (2002) used Bayesian probability model to identify the contaminant source in a five-room building. Arvelo et al. (2002) employed the genetic algorithm to locate the sources in a building with nine offices and a hallway. Zhang and Chen (2007a) used an inverse computational fluid dynamics (CFD) model with quasi-reversibility (QR) equation to identify contaminant source in an aircraft cabin and an office. They further solved inverse contaminant transport model with pseudo-reversibility (PR) method, and compared the PR method with QR method (Zhang and Chen, 2007b). Liu and Zhai (2008) proposed a probability-based CFD modelling method for identifying the location of an instantaneous source. They further developed a probability-based inverse multi-zone modelling method for identifying source location in buildings with many compartments (Liu and Zhai, 2009).

The above studies have laid a solid foundation for in depth research of more complex and realistic indoor source identification tasks. However, in these studies, only very few attempts have been made to the problems related to multiple sources. This study aims to develop a theoretical method for quickly identifying the locations and strengths of multiple constant contaminant sources by limited number of ideal sensors. With case studies of 16 scenarios of releases in a three-dimensional office, the performance of method is tested by using different layouts of sensors, total sampling periods, and sampling time intervals.

SOURCE IDENTIFICATION METHOD

Overview of the method

The problem under study is specified with the following assumptions:

1. **The indoor airflow field is steady and the contaminant can be treated as passive gas.** For most ventilated indoor environments, the airflow field can reach steady-state much faster than the

dispersion of contaminant. Normally, the airflow is turbulent and the contaminant concentration is low. The contaminant dispersion is primarily depends on the flow characteristic regardless of contaminant type. In addition, the effects of the contaminant dispersion on the airflow field are trivial. Thus, this assumption is applicable in most indoor environments.

2. **The number of potential sources is limited and their locations are known.** This assumption can be applied to a variety of contaminant dispersion scenarios, such as, the virus-spreading from patients, hazardous agents released by terrorists from supply air inlets, and the leakage of toxic gas.
3. **The emission rates of sources are constant.** The continuous releases are more common than instantaneous releases in practice. This study only consider continuous releases. For the continuous releases with changing rates, the assumption is still applicable if the change is slow and the identification is quite quick.
4. **A limited number of ideal sensors are used.** The ideal sensors are assumed to be capable of detecting any tiny concentrations without errors. Actually, the concentration below the threshold is undetectable and the random errors are inevitable by using real sensors, which would make the problem of source identification much complicated. To simplify the problem, we focus on developing a method using ideal sensors and hope it will contribute to develop more sophisticated methods using real sensor.

With the above assumptions, a theoretical method is developed based on the analytical expression of indoor contaminant dispersion presented in our previous study (Yang et al., 2004). By virtue of the analytical expression, only a limited number of time-consuming CFD simulations (equals the number of potential source locations) need to be conducted to cover each scenario in which only a single source is releasing at a nominal rate at a predefined potential location. After the limited number of CFD simulations before the release event, the method can identify the locations and emission rates of sources in real-time during the event.

Analytic expression of contaminant dispersion

For the dispersion of passive gas in steady-state airflow field, the analytic expression is (Yang et al., 2004):

$$\overline{C_p}(\tau) = C_0 + \sum_{k=1}^{K}\left\{(C_{S,k} - C_0)A_{Sk,p}(\tau)\right\} + \sum_{i=1}^{I}\left\{\frac{S_i}{Q}A_{Ci,p}(\tau)\right\} \quad (1)$$

where $C_{S,k}$ is the concentration of the k th inlet, C_0 is the initial concentration, S_i is the emission rate of the i th source, Q is the air flow rate , $A_{Sk,p}(\tau)$ is the accessibility of supply air (ASA) from the k th inlet to point p within time period τ , $A_{Ci,p}(\tau)$ is the accessibility of contaminant source (ACS) from the i th source to point p within time period τ .

ASA quantifies how the air from a supply inlet is continuously delivered to an indoor location. It is a function of the flow characteristic regardless of contaminant type and source. The ASA from the k th inlet to point p within time period τ is defined as (Li and Zhao, 2004):

$$A_{Sk,p}(\tau) = \frac{\int_0^{\tau} C_p(t)dt}{C_{S,k}\cdot\tau} \quad (2)$$

where $C_p(t)$ is the contaminant concentration of point p at moment t .

ACS quantifies how the contaminant is continuously diffused into an indoor location. It is a function of both the flow characteristic and the source location regardless of emission rate and contaminant type. The ACS from the i th source to point p within time period τ is defined as (Li and Zhao, 2004):

$$A_{Ci,p}(\tau) = \frac{\int_0^{\tau} C_p(t)dt}{C_{e,i}\cdot\tau} \quad (3)$$

where $C_{e,i}$ is the average exhausted contaminant concentration under steady-state conditions.

With the analytic expression, after the ASA from each inlets and the ACS from each source were calculated using CFD, the evolution of contaminant distribution under different supply air concentrations and emission rates of source can be obtained by simple algebra calculation. This feature of the analytic expression provides a foundation for predicting the contaminant dispersion or identifying the sources in real time.

Modelling of source identification

When the initial concentration is 0 and all the inlets concentrations are 0, Equation 1 is reduced to:

$$\overline{C_p}(\tau) = \sum_{i=1}^{N}\left\{\frac{S_i}{Q}A_{Ci,p}(\tau)\right\} \quad (4)$$

Assume the identified emission rate of i th contaminant source is S_i^* , then:

$$\overline{C_p}(\tau) = \overline{C_p^*}(\tau) + e = \sum_{i=1}^{N} S_i^*\left\{\frac{A_{Ci,p}(\tau)}{Q}\right\} + e \quad (5)$$

where $\overline{C_p^*}(\tau)$ is the calculated time-average concentration at point p by substituting S_i^* into

Equation 4, e is the discrepancy between $\overline{C_p}(\tau)$ and $\overline{C_p^*}(\tau)$.

For M measurements from sensors, we get the following linear equations:

$$\begin{cases} a_{1,1}x_1 + a_{1,2}x_2 + \cdots + a_{1,N}x_N + e_1 = b_1 \\ a_{2,1}x_1 + a_{2,2}x_2 + \cdots + a_{2,N}x_N + e_2 = b_2 \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ a_{M,1}x_1 + a_{M,2}x_2 + \cdots + a_{M,N}x_N + e_M = b_M \end{cases} \tag{6}$$

Where $a_{i,j} = A_{Ci}^{j}/Q$, $b_j = \overline{C}_j$, $x_i = S_i^*$, $i \in [1,N]$, and $j \in [1,M]$.

A nonlinear programming model can be built to identify the S_i^* as follows:

$$\begin{aligned} &\min \quad f(\mathbf{x}) = \sum_{i=1}^{M} |x_{N+i}| \\ &\text{s.t.} \quad \mathbf{Ax}=\mathbf{b} \\ &\qquad x_i \ge 0, \quad i \in [1,N] \end{aligned} \tag{7}$$

where $\mathbf{x} = (x_1, x_2, \cdots, x_N, x_{N+1}, \cdots x_{N+M})^T$,

$\mathbf{A} = (a_{i,j})_{M,N+M}$,

$\mathbf{b} = (b_1\ b_2 \cdots b_M)^T$,

$x_{N+j} = e_j$,

and $(a_{i,N+j}) = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}$, $j = 1, 2, \cdots, M$.

The model can further be transformed into a linear programming model by setting:

$$|x_{N+i}| = x'_{N+i} + x''_{N+i}, \quad x_{N+i} = x'_{N+i} - x''_{N+i} \tag{8}$$

Then,

$$\begin{aligned} x'_{N+i} &= \begin{cases} x_{N+i}, & x_{N+i} \ge 0 \\ 0, & x_{N+i} < 0 \end{cases}, \\ x''_{N+i} &= \begin{cases} 0, & x_{N+i} \ge 0 \\ -x_{N+i}, & x_{N+i} < 0 \end{cases} \end{aligned} \tag{9}$$

Substituting x'_{N+i} and x''_{N+i} into Equation 7, we get:

$$\begin{aligned} &\min \quad f(\mathbf{x}) = \sum_{i=1}^{M} x'_{N+i} + x''_{N+i} \\ &\text{s.t.} \quad \mathbf{Ax}=\mathbf{b} \\ &\qquad x_i \ge 0, \quad i \in [1, N+2M] \end{aligned} \tag{11}$$

Where

$\mathbf{x} = (x_1, x_2, \cdots, x_N, x'_{N+1}, \cdots x'_{N+M}, x''_{N+1}, \cdots x''_{N+M})^T$,

$\mathbf{A} = (a_{i,j})_{M,N+2M}$,

$\mathbf{b} = (b_1\ b_2 \cdots b_M)^T$,

$x_{N+j} - x_{N+j+M} = e_j, \quad j \in [1,M]$,

$(a_{i,N+j}) = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}$, $j = 1, 2, \cdots, M$,

and $(a_{i,N+M+j}) = \begin{pmatrix} -1 & 0 & \cdots & 0 \\ 0 & -1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & -1 \end{pmatrix}$, $j = 1, 2, \cdots, M$.

Procedure of source identification

The procedure of method is summarized as follows:

1. Calculate the steady-state flow field using CFD;
2. Calculate the distribution of ACS for each potential source using CFD. The number of CFD simulations equals to that of potential sources;
3. Solve the linear programming model (Equation 10) to obtain the emission rate of each source by using the measurements of sensors and the data obtained in Steps 1 and 2.

In practice, only Step 3 is conducted during the contaminant release event. The time-consuming Steps 1 and 2 could be conducted before the event. Note that, the ACS can also be obtained by using tracer gas experiments. The experiments may be more expensive and time-consuming but may be more accurate if they were carefully conducted.

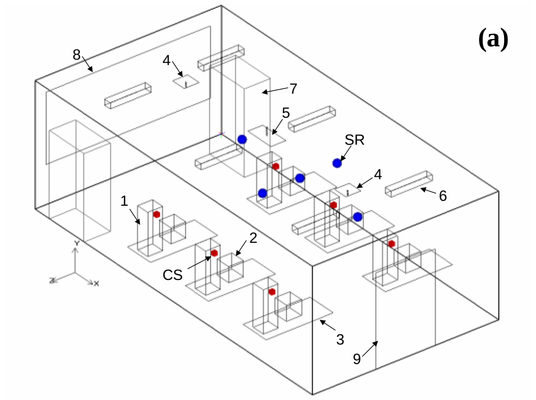
CASE STUDY

Case setup

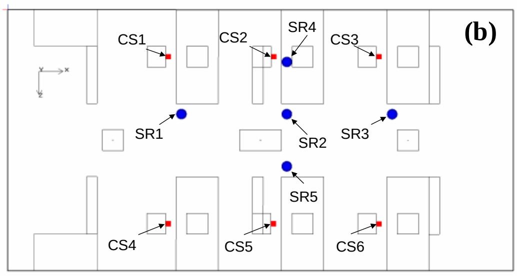
A three-dimensional office (Fig. 1) was studied to validate the method presented. There were six persons in the room and each person was sitting at a fixed place. The room was 9.6 m long (X), 3.2 m high (Y), and 5 m wide (Z) and was ventilated with two supply air inlets (0.4 m×0.4 m) and an exhaust air outlet (0.8 m×0.4 m). The supply airflow rate of the room was 0.128 m^3/s and the supply air temperature was 16 ^oC. The supply air inlets and exhaust air outlet were of the same vertical air velocity of 0.4 m/s. There were several convective heat sources indoors, including six computers, six persons, six lamps, and a window. The heat generation rates of each computer, person, and lamp were 108 W, 75 W, and 34 W, respectively, while the window contributed 220 W. For simplicity, all the four walls, the ceiling, and the floor were assumed as adiabatic boundaries.

Assume one or more infected persons in the room were spreading a certain virus. In order to find out the infected persons and protect others, a source identification system equipped with five virus sensors (SR1–SR5) was installed in the office (Fig. 1). All the sensors were assumed to be capable of detecting any low concentration without any errors.

As each person was at a fixed position, the positions of potential virus sources were certain and numbered as CS1–CS6. The positions of the sensors and potential virus sources are summarized in Table 1.



Person: 1; Computer: 2; Table: 3; Supply air inlets: 4; Exhaust air outlets: 5; Lamp: 6; Cabinet: 7; Window: 8; Door: 9; Contaminant Source: CS; Sensor: SR



Contaminant sources: CS1–CS6; Sensors: SR1–SR5

Figure 1 Schematic of the office room: (a) Three-dimensional sketch map; (b) Plane layout.

Table 1
Positions of the sensors and potential virus sources

NO.[a]	POSITION (m)		
	X	Y	Z
SR1	3.30	2.20	2.00
SR2	5.30	2.20	2.00
SR3	7.30	2.20	2.00
SR4	5.30	2.20	1.00
SR5	5.30	2.20	3.00
CS1	3.00	0.95	0.85
CS2	5.00	0.95	0.85
CS3	7.00	0.95	0.85
CS4	3.00	0.95	4.05
CS5	5.00	0.95	4.05
CS6	7.00	0.95	4.05

[a]SR1–SR5: Sensors; CS1–CS6: Potential contaminant sources

Sixteen virus-spreading scenarios were designed to test the performance of method (Table 2). For all the scenarios, the emission rate of each source was set to a constant. In practice, the emission rate may change with the development of the disease. Nevertheless, it is reasonable to take the emission rates as constants for a short time period of source identification.

Simulation tool

A commercial CFD program AIRPAK was used as simulation tool, which is customized from a general-purpose program FLUENT for indoor environment simulations. The AIRPAK has been validated by numerous indoor airflow and contaminant dispersion studies, as reported by Xu (2003). A zero-equation turbulence model (Chen and Xu, 1998) was employed to account for the indoor turbulent flow. The momentum equations were solved on non-uniform staggered grids by using a Semi-Implicit Method for Pressure-Linked Equations (SIMPLE) algorithm (Anderson, 1995). The office room under study was discretized by 56,244 hexahedral control volumes which were systematically refined to ensure the solution was grid independent.

Procedure of validation

The procedure of validation is:

1. Calculate the steady-state flow field using CFD;
2. Calculate the distribution of ACS for each potential source using CFD;
3. For each scenario with predefined emission rates of sources (see Table 2), simulate the dispersion of contaminant indoors using CFD and record the changing concentration at the positions of sensors;
4. Identify the emission rate of each source using the data obtained in Steps 2 and 3 and the linear programming model (Equation 10);
5. Evaluate the performance of method by comparing the identified emission rates with predefined ones listed in Table 2.

RESULTS

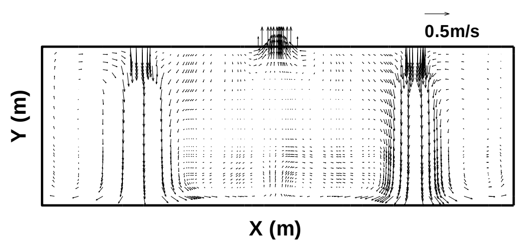


Figure 2 Airflow pattern on a vertical plane through centerline of inlets (Z = 2.5 m*)*

The steady-state flow field indoors was calculated at first. As shown in Fig. 2, the supply air injected from the two inlets to the floor, then flowed along the floor and created several vortexes, and finally was vented out from the outlet.

Followed by the calculation of flow field, the distribution of ACS for each potential source was calculated (6 CFD simulations). Fig. 3 illustrates the distributions of ACS for CS4 on a horizontal plane through the sensors at different moments.

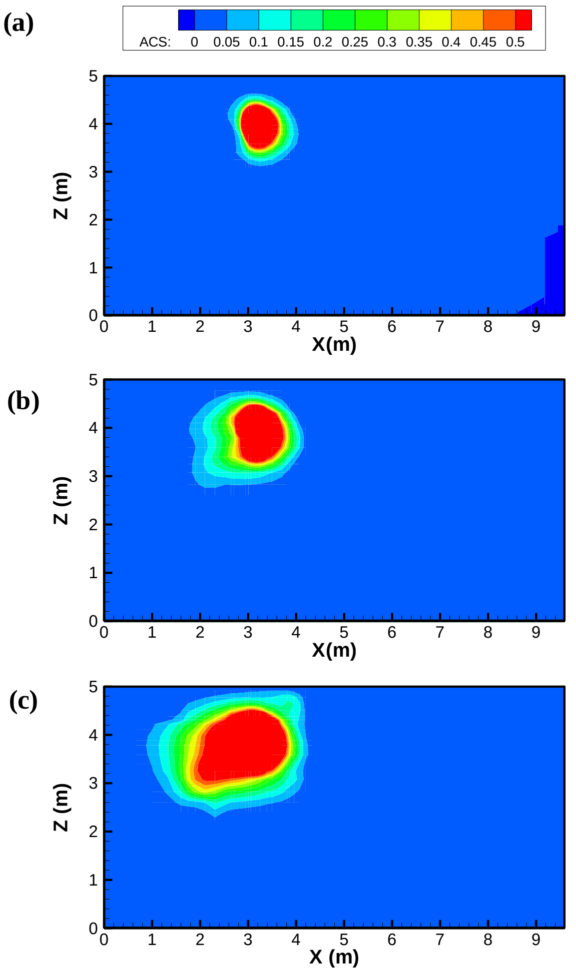


Figure 3 Distributions of Accessibility of Contaminant Source (ACS) for potential contaminant source CS4 on a horizontal plane through sensors (Y = 2.2 m*) at time: (a) 30* s*; (b) 60* s*; (c) 120* s.

Following the procedure of validation (Steps 3, 4, and 5), 16 scenarios of virus-spreading were tested by using different layouts of sensors, total sampling times, and sampling intervals. Table 3 lists the results using five sensors (SR1–SR5). To quantify the accuracy of the identifications, a series of indexes called Scale of Relative Errors (SRE) are defined as follows:

$$SRE1_i = \frac{S_i' - S_i}{\max\limits_{1\le i\le N}(S_i)} \qquad (11)$$

where S_i and S_i' are the actual and identified emission rate of the i th source, respectively; N is the number of all the potential sources. $SRE1_i$ reflects the level of relative error between the actual and identified emission rate of the i th source. A smaller value of $SRE1_i$ means a more accurate identification of i th source.

$$SRE2 = \frac{\sum_{i=1}^{N} |SRE1_i|}{N} \qquad (12)$$

$SRE2$ reflects the average level of $|SRE1_i|$ ($1 \le i \le N$). A smaller value of $SRE2$ indicates a more accurate identification for all the potential sources from the respect of overall average.

$$SRE3 = \max_{1\le i\le N} |SRE1_i| \qquad (13)$$

$SRE3$ reflects the maximum level of $|SRE1_i|$ ($1 \le i \le N$). A smaller value of $SRE3$ indicates a more accurate identification for all the potential sources from the respect of maximum relative error.

The SRE indexes listed in Table 3 show that the identifications were very accurate for all the scenarios. The results indicate that the method has the potential to obtain accurate results for the scenarios involving one or multiple contaminant sources by using a limited number of sensors.

DISCUSSION

The effects of the number and positions of sensors

To quantify the overall accuracy of the results for all the 16 scenarios, an index based on SRE2 is defined as follows:

$$SRE4 = \sum_{j=1}^{M} SRE2_j \Big/ M \qquad (14)$$

where M is the number of all the scenarios tested; $SRE2_j$ is SRE2 for j th scenario. A smaller value of $SRE4$ indicates an overall more accurate identification for all the scenarios tested.

Fig. 4 shows the SRE4 index for all the 16 scenarios with different sensor layouts. When a single sensor was used, the best results (using SR1) differed greatly from the worse results (using SR3). When multiple sensors were used, the SRE4 index changed greatly with the number and positions of sensors. Unexpectedly, the results of sensor layout 1 (composed of layout 2 and SR3) were worse than that of layout 2 in terms of SRE4 value. A possible explanation is that SR3, which corresponded to the worst results when used alone, had an adverse effect on the overall performance of the existing sensor system. In summary, the above results indicate that the accuracy of source identification is closely related to the number and positions of sensors in use. In addition, additional sensors may not improve the accuracy of identification, if they are not placed at proper positions.

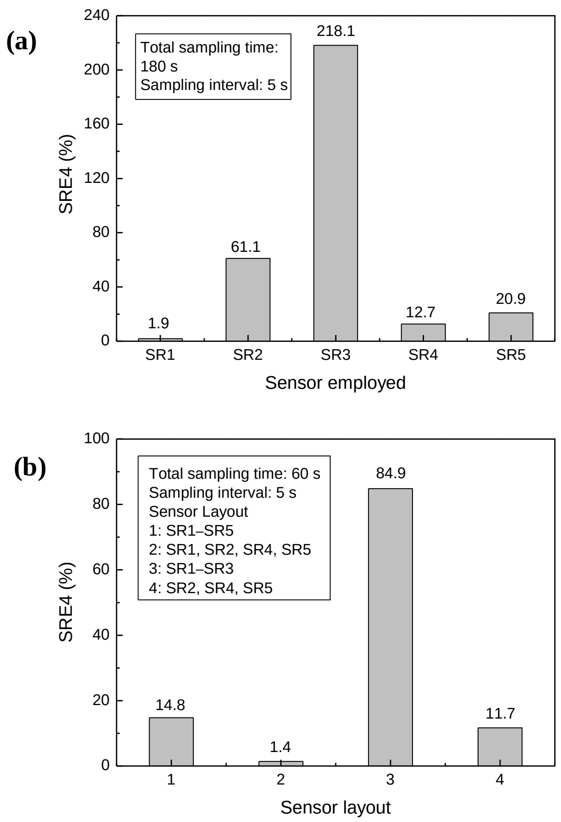


Figure 4 Scale of relative errors (SRE4, see Equation 14) for all the 16 scenarios by using: (a) a single sensor, (b) multiple sensors.

The effects of the total sampling time

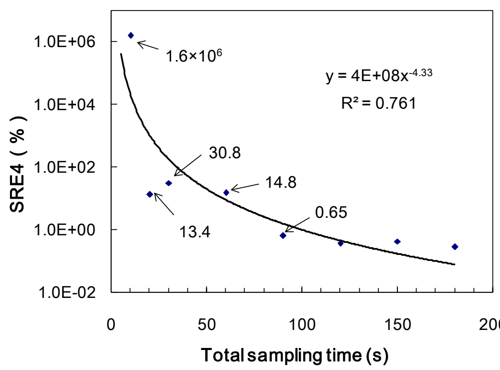


Figure 5 Variation of SRE4 for all the 16 scenarios with total sampling time. (Sensors used: SR1–SR5; Sampling interval: 5 s)

As shown in Fig. 5, SRE4 for all the 16 scenarios decreased as a power law function of the total sampling time. When the total sampling time was 10 s, extremely large errors (SRE4 = 1.6×10^{6}%) were found. As the total sampling time was extended to 20 s, the errors decreased dramatically to an acceptable level (SRE4 = 13.4%). When the total sampling time was larger than 90 s, the identifications were extraordinarily accurate (SRE4 $\leqslant$ 0.65%). A possible explanation for such a surprisingly high accuracy is the use of ideal sensors in this case. The above results indicate that the accuracy of source identification can be improved by extending the total sampling time. In addition, there is a threshold of total sampling time for reaching a desirable accuracy of source identification.

The effects of the sampling interval

Fig. 6 shows the effects of sampling interval on the performance of method. First, the computing time corresponding to each sampling interval was very short (Fig. 6a), and expected to meet the needs of identifying the sources in a range of seconds for most applications. Next, the average computing time decreased as a power law function of the sampling interval (Fig. 6a). In addition, as shown in Fig. 6b, with the increase of sampling interval, the accuracy of identification (refer to SRE4) was not decreased. The above results indicate that increasing the sampling interval has the potential to greatly reduce computing time without sacrificing the accuracy of identification.

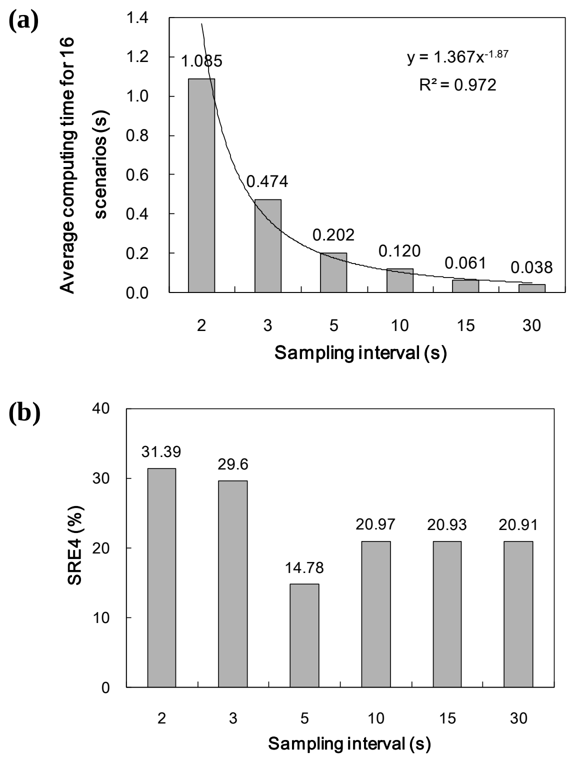


Figure 6 Effects of sampling intervals on (a) average computing time, and (b) SRE4 (see Equation 15) for all the 16 scenarios. (CPU: Intel(R) Core(TM)2 T7200 @ 2.00GHz; Sensors used: SR1–SR5; Total sampling time: 60 s)

CONCLUSION

This study leads to the following conclusions:

1. The method has the potential to rapidly and accurately identify the locations and strengths of

multiple constant contaminant sources indoors by using a limited number of ideal sensors.

2. The accuracy of identification is closely related to the layout of sensors (number and positions). In addition, the accuracy of identification would be improved only if the additional sensors are placed at proper positions, which shows the importance of developing a method to optimize the layout of sensors.
3. Higher accuracy of identification can be reached by using longer total sampling time. To reach a desirable accuracy of identification, the total sampling time should exceed a certain threshold.
4. The computing time of the method (with a personal computer) is expected to be a few seconds for most applications. For complex cases, the computing time can be reduced without decreasing the accuracy of identification by increasing the sampling interval.

This study may help to develop more sophisticated methods for identifying multiple sources by using real sensors as well as methods for optimizing the layout of sensors.

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REFERENCES

Alifanov, O. M. 1994. Inverse heat transfer problems. New York, Springer-Verlag.

Anderson, J. 1995. Computational fluid dynamics, McGraw-Hill, New York, USA.

Arvelo J, Brandt A, Roger R P, et al. 2002. An enhancement multizone model and its application to optimum placement of CBW sensors. ASHRAE Trans. 108 (2): 818–825.

Chen, Q., Xu, W. 1998. A zero-equation turbulence model for indoor airflow simulation, Energ. Buildings 28 (2): 137–144.

Li, X., Zhao, B. 2004. Accessibility: a new concept to evaluate the ventilation performance in a finite period of time, Indoor Built Environ. 13 (4): 287–293.

Liu, X., Zhai Z. J. 2009. Prompt tracking of indoor airborne contaminant source location with probability-based inverse multi-zone modeling." Building and Environment 44 (6): 1135–1143.

Liu, X., Zhai Z. 2007. Inverse modeling methods for indoor airborne pollutant tracking: literature review and fundamentals. Indoor Air 17 (6): 419–438.

Liu, X., Zhai Z. 2008. Location identification for indoor Instantaneous point contaminant source by probability-based inverse Computational Fluid Dynamics modeling. Indoor Air 18 (10): 2–11.

Mahar, P. S., Datta B. 2000. Identification of pollution sources in transient groundwater systems. Water Resources Management 14 (3): 209–227.

Seibert, P., Frank, A., Kromp-Kolb H. 2002. Inverse Modelling of Atmospheric Trace Substances on the Regional Scale with Lagrangian Models. Proceedings from the EUROTRAC-2 Symposium 2002, Garmisch-Partenkirchen, Germany.

Sohn, M. D., Reynolds, P., Singh, N., et al. 2002. Rapidly locating and characterizing pollutant releases in buildings. J. Air & Waste Manage. Assoc. 52 (12): 1422–1432.

Xu, L. 2003. Effectiveness of hybrid air conditioning system in a residential house, Ph.D. thesis, Waseda University, Japan

Yang, J., Li, X., Zhao, B. 2004. Prediction of transient contaminant dispersion and ventilation performance using the concept of accessibility, Energ. Buildings 36 (3): 293–299.

Zhang, T. F., Chen, Q. 2007a. Identification of contaminant sources in enclosed environments by inverse CFD modeling. Indoor Air 17 (3): 167–177.

Zhang, T. F., Chen, Q. 2007b. Identification of contaminant sources in enclosed spaces by a single sensor. Indoor Air 17 (6): 439-449.

Table 2
Scenarios of virus-spreading [a]

SCENARIO	EMISSION RATE OF EACH SOURCE (units/s)					
	CS1	CS2	CS3	CS4	CS5	CS6 [b]
1	50	0	0	0	0	0
2	0	50	0	0	0	0
3	0	0	50	0	0	0
4	0	0	0	50	0	0
5	0	0	0	0	50	0
6	0	0	0	0	0	50
7	50	50	0	0	0	0
8	50	0	50	0	0	0
9	0	0	50	0	50	0
10	50	50	50	0	0	0
11	50	50	0	50	0	0
12	50	0	50	0	0	50
13	50	50	50	50	0	0
14	50	0	50	50	0	50
15	0	50	50	50	50	50
16	50	50	50	50	50	50

[a] The virus source with an emission rate greater than zero is highlighted in grey background; [b] CS1–CS6: Potential contaminant sources

Table 3
Identification results by using five sensors [a]

SCENARIO	RELATIVE ERROR INDEX, SRE1 (%)						RELATIVE ERROR INDEX (%)	
	CS1	CS2	CS3	CS4	CS5	CS6	SRE2	SRE3
1	-0.02	0.00	0.00	0.00	0.00	0.02	0.01	0.02
2	0.00	0.00	0.00	0.00	0.00	1.30	0.22	1.30
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	-0.02	0.00	0.00	0.00	0.02
5	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.01
6	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.01
7	-0.05	0.00	0.00	0.00	0.00	1.51	0.26	1.51
8	-0.10	0.00	0.00	1.41	0.00	0.00	0.25	1.41
9	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.01
10	-0.02	0.00	0.00	0.00	0.00	2.70	0.45	2.70
11	0.74	0.00	0.00	-15.70	0.00	0.00	2.74	15.70
12	-0.04	0.00	0.00	0.24	0.00	-0.16	0.08	0.24
13	0.03	0.00	0.00	-1.11	0.00	2.04	0.53	2.04
14	-0.05	0.00	0.00	0.64	0.00	-0.13	0.14	0.64
15	0.01	0.00	0.00	-0.43	-0.02	2.50	0.49	2.50
16	0.04	0.00	0.00	-0.99	-0.02	2.26	0.55	2.26

[a] Five sensors (SR1–SR5) were employed. The total sampling time was 120 s, and the sampling interval was 5 s. The table cell highlighted in grey background indicates the emission rate of the corresponding source was greater than zero.